REPORT DOCUMENTATION PAGE

Form Approved OMB No. 0704-0188

	2. REPORT DATE	3. REPORT TYPE AND DATES COVERED
	September 9,1993	Reprint

4. TITLE AND SUBTITLE
Agricultural Production Monitoring in the Sahel Using Remote Sensing: Present Possibilities and Research Needs

5. FUNDING NUMBERS
PE 62101F
PR 6670
TA GR
WU 16

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8. PERFORMING ORGANIZATION REPORT NUMBER
PL-TR-93-2190

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)

10. SPONSORING/MONITORING AGENCY REPORT NUMBER

11. SUPPLEMENTARY NOTES
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Reprinted from Journal of Environmental Management(1993) 38, 301-322

12a. DISTRIBUTION/AVAILABILITY STATEMENT
Approved for public release; Distribution unlimited

12b. DISTRIBUTION CODE

13. ABSTRACT *(Maximum 200 words)*

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14. SUBJECT TERMS	15. NUMBER OF PAGES
Agricultural production, Information system, Remote sensing, Sahel	22
	16. PRICE CODE

17. SECURITY CLASSIFICATION OF REPORT	18. SECURITY CLASSIFICATION OF THIS PAGE	19. SECURITY CLASSIFICATION OF ABSTRACT	20. LIMITATION OF ABSTRACT
UNCLASSIFIED	UNCLASSIFIED	UNCLASSIFIED	SAR

PL-TR-93-2190

Journal of Environmental Management (1993) **38**, 301–322

Agricultural Production Monitoring in the Sahel Using Remote Sensing: Present Possibilities and Research Needs

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Received 2 *July* 1992

The main objective is to review the current status of research related to the monitoring of agricultural production in the Sahel (west Africa). The Sahel suffers from frequent shortages of food. It is therefore important to have a tool to monitor environmental variables, and thus crop production, during the agricultural season. Satellite remote sensing can contribute significantly to such a system by collecting information on crops and on environmental variables at a sub-continental geographical scale and with a high temporal frequency. One part of the problem is to estimate crop acreage. The technique of area-sampling frame has to be adapted to the Sahelian landscape, which is dominated by traditional farming systems. The second part is to estimate crop yields. Three main approaches exist: statistical, semi-deterministic or deterministic. The use of vegetation indices is discussed as well as techniques to derive biophysical variables from remotely-sensed data. Finally, the integration of these remote-sensing techniques with crop-growth models is discussed and some research needs are identified. It is argued that the quantitative assessment of agricultural production in the Sahel should be based on the integration of remotely-sensed data with semi-deterministic agrometeorological models. This approach will allow a regionalization of the production estimates.

Keywords: agricultural production, information system, remote sensing, Sahel.

1. Introduction

Scientific research on development issues and environmental concerns has become increasingly specialized and fragmented. To compensate for this inevitable trend, there is a growing need for parallel activities aimed at producing a synthesis of the on-going research. The purpose of such a synthesis is to link the different pieces of research together and to evaluate their compatibility and cohesiveness. This paper attempts to

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integrate the research activities related to the monitoring of agricultural production in west Africa, at the scale of the Sahel. Only those methods related to the monitoring of rainfed agriculture will be analyzed. The result will be the definition of operational methods and the identification of research needs.

Famines in Africa are usually localized events and rarely occur across very large areas. Regions suffering from food shortages are sometimes adjacent to regions with an agricultural surplus. The first solution to famines and malnutrition should thus be the increase in interregional fluxes of food inside Africa. However, the infrastructure for the transportation and commercialization of agricultural surplus between regions is generally lacking in Sudano–Sahelian zones. Thus, a better exploitation of interregional complementarities to face food shortages requires a considerable effort to mobilize the necessary resources: market incentives to collect agricultural surplus, roads and means of transportation, stocking facilities and distribution networks. A time lag will always exist between the onset of food shortages and the import of agricultural surpluses from neighboring zones. There is a fundamental need to provide local parties with timely and accurate information on the status of agricultural crops across a very large area. Existing famine early-warning systems qualitatively anticipate food shortages. Most of these systems, reviewed by Walker (1989) and Hutchinson (1991), have chosen to view early-warning as distinct from crop forecasting or agricultural production estimation. Consequently, they have adopted simple methods based on a qualitative assessment of crop performance. Lower levels of accuracy are accepted in exchange for shorter reporting times and lower costs (Hutchinson, 1991).

In addition to these qualitative efforts, there is also a need for information systems to estimate agricultural production quantitatively in regions which are not affected (as well as those affected) by a lower than usual agricultural production. Such systems would allow the identification of regions with an agricultural surplus and the quantification of this surplus. With an objective of solving food shortages with local resources rather than food aid from foreign donors (which should be required only in extreme conditions), this information requirement outstrips the capability of existing famine early-warning systems. The needed information on agricultural production should have the following characteristics:

1. Coverage of large areas—i.e. information at a small geographical scale.
2. Delivery of the information on agricultural production a few weeks before the harvest (after the heading of the crops)—estimates of final crop yield rather than long-term early warning.
3. Quantitative estimation of agricultural production rather than qualitative comparison of crop years.
4. Regionalization of the information—the spatial variability of agricultural production is the critical information needed to organize interregional transfers of food; ideally, the areal units for reporting should be related to existing administrative units.
5. An easy and rapid transmission of the information should be possible with the existing infrastructure of telecommunication in Sahelo–Sudanian regions.

The objective of this paper is to survey the methods that would allow a reliable and quantitative estimation of agricultural production with a sufficient time threshold to achieve food security. This approach differs from conventional methods of establishing agricultural statistics in: (1) the timeliness of the estimation; and (2) the geographic coverage of such information. Given these two characteristics, satellite remote sensing plays an obvious and important role in such an effort. Only the methods applicable for rainfed agriculture will be surveyed. Methods to monitor irrigated crops are analyzed in other publications (for instance, Tennakoon *et al.*, 1992).

2. General structure of a system for agricultural production monitoring

Agricultural production is estimated by multiplying crop acreages by the yields for each crop in a given area. The estimation of these two regionalized variables defines the two main and relatively independent components of the information system. These two variables can be estimated using a combination of remotely-sensed data and ground data.

2.1. CONTRIBUTION OF REMOTE SENSING

The research on the contribution of remote sensing to crop forecasting and to the estimation of agricultural production generally concludes that, at the present level of technology: (1) no method exists to estimate crop acreage reliably from satellite data in regions of traditional agriculture without a heavy complement of ground data collection; and (2) spectral data alone have not proven satisfactory in estimating crop yields.

Concerning the first point, various attempts to classify high-resolution, remotely-sensed data in order to discriminate between crops in Africa have failed. The reasons are that the spectral separability of tropical crops is low, and, moreover, the traditional farming practices of the region are not compatible with the spatial resolution of existing high-resolution Earth observation satellites (20 m for SPOT multispectral data or 30 m for Landsat Thematic Mapper data). The major obstacles to a spectral classification of crops in a landscape dominated by traditional farming practices are: small and irregular field sizes, mixture of crops within fields, cultivation under tree cover and contiguity of fallows with cultivated fields. In addition, the probability of acquiring satellite data over Sahelo–Sudanian zones during the growing season is extremely low, given the persistent cloud cover. The large-scale operational use of satellite data for crop inventory is not practicable in the region without the support of an intensive field campaign (Revillon, 1987; Lambin, 1988; Imbernon *et al.*, 1988), although some localized experimental projects have succeeded and Azzali (1990) successfully classified and discriminated fields of maize in Zambia based on a multitemporal analysis of a vegetation index calculated from Landsat Thematic Mapper data.

Concerning the estimation of crop yields, the major difficulty in using remotely-sensed data lies in the spatial and temporal instability of the relationship between crop yields and spectral indices (Bartholomé, 1988). Equally variable are the major determinants of crop yield such as rainfall, soil moisture, soil fertility and land use practices. As a result, a remote-sensing model to estimate crop yield requires considerable calibration with numerous field data. Moreover, the sensor and atmospheric factors affecting spectral indices measurements would have to be neutralized. Finally, although remote-sensing methods allow reliable measurements of primary production, the harvest yield depends on the proportion of the production ultimately diverted to the harvested part of the crop. This proportion, measured by the harvest index, cannot be estimated by remote-sensing techniques (Prince *et al.*, 1990). An alternative to using pure remote-sensing models to estimate crop yield is to base the yield estimation on deterministic crop growth models or semi-deterministic agrometeorological models, and to estimate some of the input biophysical variables required by these models through remote-sensing methods which are calibrated by ground observations.

Despite these realistic assessments, it is possible to extract useful information from the synoptic view and repetitive acquisitions of satellite data as long as it is recognized that the analysis of remotely-sensed data must be integrated with a ground-sampling strategy and with crop-growth models. The question is how to minimize the need for ground-collection systems or how to optimize the ground campaign for a given degree of accuracy of the estimations. Remote sensing can be used as a powerful spatial extrapolation tool if properly integrated in an information system with ground-calibration data and accurate data-processing methods.

2.2. COMPONENTS OF THE INFORMATION SYSTEM

As shown in Figure 1, the final component of the information system is a module to estimate agricultural production by extrapolating, at different geographic levels, the product of the crop acreage and the estimated yield. This module will be based on: (1) an area-sampling frame; and (2) a yield-estimation model. An area-sampling frame is a method for estimating crop acreages. It is based on a multilevel stratification scheme to determine the spatial sampling of an area. The stratification procedure delineates homogeneous zones in order to minimize the intra-stratum variance of the variable to be estimated. A yield-estimation model should be based on a crop growth model or an agrometeorological model and should be connected upstream to several sub-systems which estimate biophysical input data such as rainfall, leaf area index, air temperature, etc. These sub-systems can be ground-based or based on remote-sensing models. If the variables are regionalized, they can be stored in a geographic information system which would provide the best framework in which to organize the database and to connect it with data analysis functions. In the next sections we examine the different sub-systems separately.

3. Spatial stratification scheme

Estimation of crop yield and crop acreage requires the collection of a sample of statistically representative ground data. For the Sahel, the collection of ground data on agricultural production is a difficult task because of the size of the region and the diversity of farming systems within its boundaries. A solution to sampling in a heterogeneous landscape would be to apply a multilevel spatial stratification procedure to delineate homogeneous zones according to criteria related to crop acreage and/or crop yield prior to making ground measurements. This method, known as "area-sampling frame", was developed in 1938 for the United States and has been applied in temperate regions of intensive mechanized agriculture (for example, Holko and Sigman, 1984; Ministry of Agriculture and Forestry, Italy, 1989) as well as in tropical regions (Hassan *et al.*, 1987; SYSAME, 1990). However, Hassan and Wigton (1990) reported difficulties in the application of the area-sampling frame method to areas of traditional agriculture in Sudan. Redondo *et al.* (1984) had similar difficulties in Argentina, where the natural spatial heterogeneity of agricultural regions was too high. The area-sampling frame method was designed for regions with a high occupation density. These conditions are not met in Sahelian regions and, thus, the area-sampling frame must be adapted. A common spatial stratification scheme for crop acreage estimation and yield estimation is

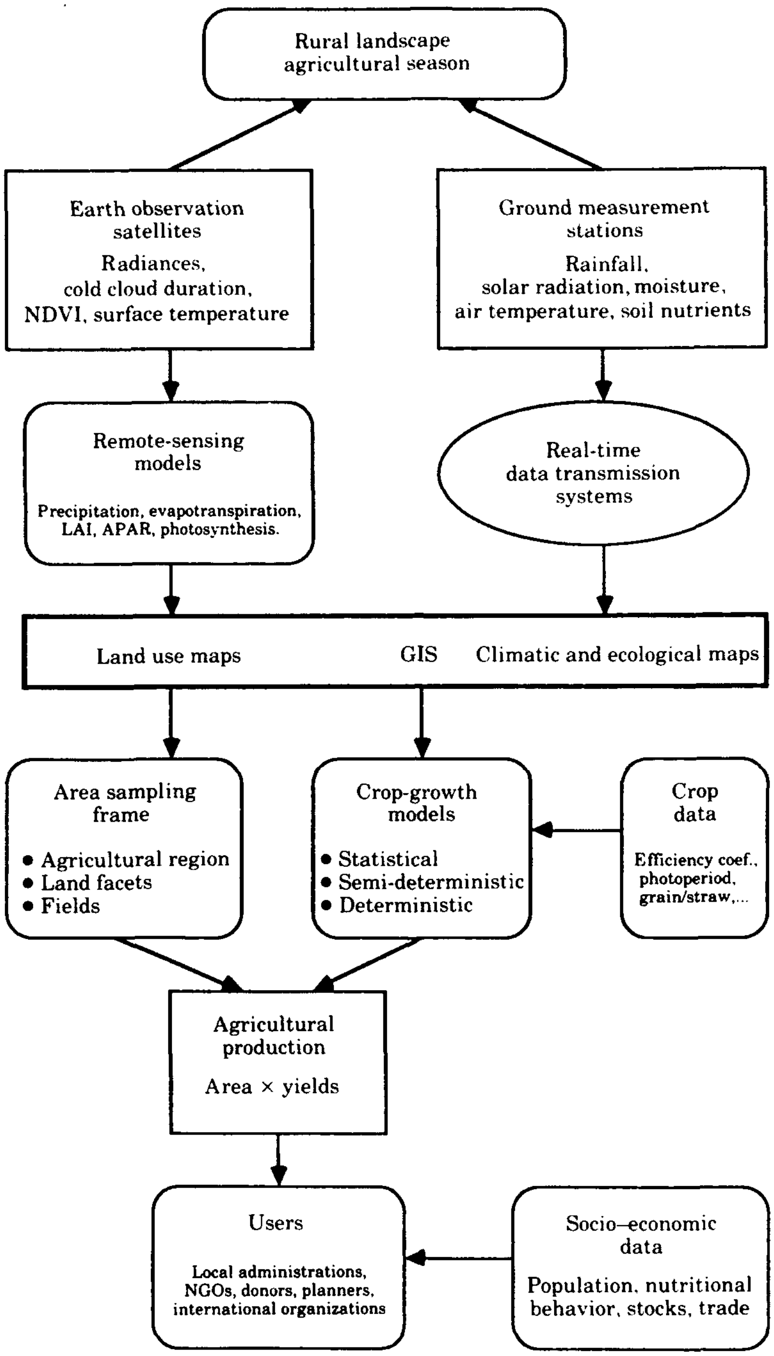

Figure 1. General structure of an information system for agricultural production monitoring.

desirable in order to use a single extrapolation procedure and field campaign strategy for the two variables.

Prior to stratification, a base map of the area first needs to be created. Because of the size of the Sahel, remote-sensing images are the most practical source of information.

AVHRR LAC data, with a spatial resolution of 1·1 × 1·1 km, would provide adequate coverage. Second, agricultural and non-agricultural regions have to be differentiated. The area which is not under cultivation has to be removed from the surface which is sampled. Supervised classification techniques applied to AVHRR LAC data can be used to block out areas such as rangelands, urban areas and river valleys.

Two classes of criteria can be used to determine a multilevel stratification scheme. The first is based on land use practices and farming systems; the second class of criteria focuses on physical characteristics such as soil types, topography and moisture availability. The stratification scheme should follow the three organizational levels of the Sahelian landscape as defined by Bartholomé (1986): the agricultural region, the land facet and the field. To be effective, the stratification should reduce the variance of crop acreage and crop yield within each stratum. Lambin and Lamy (1986) have shown that land use practices can be related to spatial patterns of the fields as detected on Landsat MSS images. This criterion can be quantified and used to segment the region at a small geographical scale into homogeneous agricultural regions. At the second level of stratification, land facets are defined by physiographic parameters in order to generate zones of uniform crop potential and soil fertility. These units can be mapped using supervised classification techniques on SPOT imagery or through aerial photograph interpretation combined with soil map analysis (Bartholomé, 1986; Lambin, 1988). In the "Africa Early Crop Warning System" of the Canadian Agency of International Development (CIDA), a stratification based on regions with a uniform productivity has been performed using FAO's soil and vegetation maps and AVHRR remotely-sensed data (Hanna and Mack, 1986). One unresolved problem of spatial stratification in regions of traditional extensive agriculture is the differentiation between permanent and itinerant agriculture. It is desirable to adopt a different sampling rate for these two types of farming practices, but fallows are difficult to recognize on remotely-sensed data.

The total potentially arable land is a rather static measurement. Thus, the base map and the stratification scheme should not be produced every year; an update every 5 to 10 years is sufficient. Once the stratification is completed, sample units, or fields, should be selected from each zone. Crop acreage and input variables for yield-estimation models are obtained from ground surveys. Sample data are collected by either the transect or segment method. Both methods have the advantage of decreasing campaign costs through the aggregation of a restricted number of observations either along a line (transect) or over an area (segment).

4. Remote sensing of biophysical input data to yield-estimation models

The main constraint to yield estimation at the regional or sub-continental scale is not the availability of appropriate yield-prediction models, but rather the availability and accuracy of the input data for these models. The use of remotely-sensed data to estimate biophysical variables which are related to agricultural production has several advantages: a synoptic view over large regions, the digital character of the data which allows computer-processing methods to be applied, the possibility of near-real-time transmission of the data and the potential for a centralized data-processing unit to facilitate the assessment and control of the quality and accuracy of the data at all levels of the processing chain. A review of the main methods for estimating the variables related to agricultural production follows. These variables fall into three main categories: information on farming practices, climatic data and soil data.

4.1. FARMING SYSTEMS SURVEY

Farming systems include the strategies adopted by cultivators to adapt to environmental and socio–economic constraints. Such adaptations include selection of: (1) crop types and varieties; (2) techniques to restore or improve soil fertility; and (3) the level of intensity of cultivation. Knowledge of these strategies contribute to the determination of crop yields. In addition, farming practices determine important variables for yield-estimation models such as the date of sowing, the density of crops in the fields, the amount and type of external agricultural inputs, the reduction of solar irradiance on crops grown under tree cover, the possible decline in organic-matter content of the soil due to inappropriate management practices, etc. A field survey of farming systems is thus a very important component for monitoring agricultural production. Socio-economic data on population, food stocks or market prices also have to be collected to assess the food security status of a region. Remote sensing can be used to design a sampling strategy to collect these data (see Section 3) and to suggest hypotheses on observable variables such as soil erosion, size and pattern of the fields, and rate of occupation of the land. For example, Guyer and Lambin (1993) could discriminate tractor-cleared fields from hand-cleared fields in a region of Nigeria by using shape criteria derived from multispectral SPOT data.

4.2. RAINFALL ESTIMATION

In the Sahelian zone of Africa, where average annual rainfall ranges from 150 to 600 mm, water is a major limiting factor in agriculture. The vastness of the area and the rapid development of weather patterns within the Inter-tropical Convergence Zone present a multitude of problems in obtaining accurate ground measurement of rainfall using traditional meteorological tools. Patterns of rainfall in the Sahel show considerable spatial variability over relatively short distances and rain gauges across the region are too sparsely placed to yield consistently reliable data (Flitcroft *et al.*, 1989). In much of the Sahel, there may be only one rain gauge per 10 000 km^2. The minimum required spacing of rain gauges is 1 per 1000 km^2 and even that density is not sufficient when rainfall is sporadic and spatially variable (Milford and Dugdale, 1990). Because of the variable nature of the rainfall pattern in the Sahel, it is difficult to interpolate values between point measurements. Research shows that the correlation between rainfall measurements falls off rapidly with distance from a point-measurement site. Although the use of kriging techniques has improved researchers' understanding of the spatial correlation structure of the immediate areas in which rainfall is occurring, interpolation methods can only be used in areas that are fairly small relative to the size of the storms.

These difficulties notwithstanding, point measurements from rain gauges can be used to calibrate, adjust and verify area estimates of rainfall derived from remotely-sensed data. Several rainfall estimation methods using remotely-sensed data are based on cloud studies from data in the visible and thermal infrared spectral channels. Satellite sensors, measuring radiation in these wavelengths, can be used for identification of cloud line growth, cloud temperature, cold cloud duration, cloud edge temperature gradient, cloud temperature in excess of a threshold, and cloud type, thickness and height. Research techniques based on cloud temperatures and appropriate temperature thresholds can be used to identify dry spells (Milford and Dugdale, 1990). Cold cloud statistics are the basis for several methods of assessing the potential of storm systems to produce rainfall (Barrett and Martin, 1981; Milford and Dugdale, 1990; Rosema, 1986; Assad *et al.*, 1987). The statistics are based on AVHRR or Meteosat visible and or thermal infrared data. Using visible imagery, the observation of cloud growth and development derives from the relationship between cloud brightness and cloud thickness. Cloud thickness is an indication of water content and probability of rain. Studies based on thermal infrared data make use of the relationship between area precipitation and the duration of cold cloud pixels (CCD), a cloud temperature property which indicates, over time, its rainbearing potential (Snijders, 1991).

The Tropical Agricultural Meteorology using SATellite (TAMSAT) program from the University of Reading (U.K.) involves the definition of high cloud areas where cloud temperatures fall below a certain threshold. In TAMSAT, the Meteosat CCD values are converted to rainfall amounts, by using regression parameters which are derived from the comparison of ground and satellite data (Flitcroft *et al.*, 1989). This method works better at dry, higher latitudes of the northern Sahel (Snijders, 1991). Rosema (1990) has extended this method by adding an indication of the latitude of the pixel under consideration. Huygen (1989) has demonstrated in Zambia that the parameters of the linear regression vary from one 10-day period to the next. ADMIT, the fully-automated data-processing program developed by University of Bristol associates, provides accurate rain estimates at the lower latitudes of the southern Sahel where rainfall is heavier (Snijders, 1991). Two significant differences between this method and the CCD methods are the use of AVHRR data and the identification of raindays rather than duration of cold cloud pixels. ADMIT uses a classification scheme to identify wet pixels and dry pixels using thresholds applied to AVHRR images in the visible and thermal infrared bands. A wet pixel is assigned a rainfall estimate value equal to the climatological mean for that location. Improved results were obtained by using mean rain per rainday data rather than climatological means.

Studies in Senegal have shown that the accumulated soil surface temperature over a short period of time (10 to 30 days) is correlated to precipitation during that period (Assad *et al.*, 1987; Seguin *et al.*, 1989). This is related to the cooling effect of rainfall on soil. The addition of accumulated surface temperature improves the CCD method for rainfall estimation (Guillot, 1990).

4.3. EVAPOTRANSPIRATION ESTIMATION

Rainfall itself is not the most important parameter in crop-yield estimation: what really needs to be known is the soil moisture and water availability for plant growth. In the Sahel, moisture availability and soil nutrients are the primary limiting factors to agricultural production (Breman and de Wit, 1983). Therefore, the accurate measurement of water availability is a key to accurate crop-growth modeling. Water availability for plant growth is a complex function of rainfall, hydrology, soil properties, temperature-related evaporation and plant transpiration and assimilation capabilities. Milford and Dugdale (1990) have shown that the amount of rainfall infiltrating into the soil is not uniform: local runoff redistributes the rain. Rosema (1990) has compared precipitation maps with evapotranspiration maps, both derived from satellite data, and a number of differences can be observed between the two maps. Only when available moisture (rainfall that hasn't drained away) exceeds evapotranspiration (water vapor loss due to soil evaporation and plant transpiration) is there sufficient moisture for photosynthesis and plant growth. Evapotranspiration is, therefore, a crucial variable in crop-growth models. Because soil evaporation is, on the average, small, evapotranspiration is a good estimator of transpiration and therefore of crop growth.

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Evapotranspiration is equivalent to the latent heat of evaporation which functions as part of the energy balance equation. The energy balance equation states that the net radiation (Q_N) of the earth (absorbed solar energy, and emitted, and reabsorbed long-wave radiation) is equal to the flux of latent heat of evaporation (Q_{ET}), sensible heat flux (Q_H) and conductive soil heat flux (Q_G). The basic energy budget equation (Oke, 1987) is therefore rearranged as the following:

$$Q_{ET} = Q_N - Q_G - Q_H.$$

Net radiation and soil heat flux can be determined from micrometeorological measurements or remote-sensing techniques. However, simple estimates of sensible heat flux (which is a function of windspeed, roughness and atmospheric stability) are more difficult to obtain. Because evapotranspiration is usually required (at a variety of spatial resolutions) as a daily quantity and the remotely-sensed component data is of an infrequent and instantaneous nature, various methods to integrate a basic energy model over a day have been developed. Rather than explicitly measuring sensible heat and soil heat in a deterministic fashion, semi-empirical energy models are most commonly used (Jackson *et al.*, 1977). These models assume that the difference in daily values of latent heat flux and net radiation is linearly related to the stress degree day (or the difference in skin and air temperature at solar noon) and take the following form:

$$Q_{ETdaily} - Q_{Ndaily} = A + B(T_s - T_a).$$

Sequin and Itier (1983) have shown that these models have a theoretical basis and that the empirically-derived constant B contains information on the roughness, stability and wind speed. A number of authors have elaborated on these basic equations. The techniques of Rosema (1986, 1990), Thunnissen and Nieuwenhuis (1990) and Lagouarde (1991) seem to strike the best balance between operational expediency and physical accuracy in providing an evapotranspiration value.

Rosema (1986, 1990) takes a more deterministic approach to produce daily continuous evapotranspiration maps. When a pixel is cloud covered, evapotranspiration is calculated with the Penman–Monteith equation (Oke, 1987) and a soil dry depth model. When a pixel is clear, the semi-empirical method above is used with the constant B determined from windspeed, temperature and an estimation of roughness and vegetation cover derived from recent relative evapotranspiration measures. Although this method is computationally intensive, it has been employed with success in regions of the Sahel by using atmospherically-corrected Meteosat data. The physical model is not site specific and can be applied across the Sahel. It does, however, require ancillary meteorological data such as air temperature, windspeed and humidity which are difficult to acquire consistently.

Thunnissen and Nieuwenhuis (1990) use potential evapotranspiration and replace the midday stress degree day with the temperature difference between a crop transpiring at actual soil conditions (remotely sensed) and a crop transpiring at optimal soil conditions. They use a separate deterministic simulation model to calculate realistic empirical B constants. By normalizing the energy balance equation by the potential evapotranspiration, a B constant which is less sensitive to temperature and humidity is calculated. However, this per pixel constant is still very sensitive to wind speed, crop height and roughness and requires full soil coverage. Although this technique shows promise in small regional applications, the requirement for fine-resolution crop height and roughness values and for variable wind-speed values over the Sahel is unrealistic. Furthermore, crop coverages in the Sahel are quite low, which also adversely affects the accuracy of the estimated evapotranspiration values. However, Caselles *et al.* (1992) have recently proposed a modification of the *B* constant which uses the satellite observation geometry to compensate for variations due to partial soil coverage.

Lagouarde (1991) also uses the semi-empirical energy model, with skin temperatures from AVHRR and air temperatures from meteorological stations. The constant *B* is empirically derived for a variety of roughness lengths. Evapotranspiration values can then be calculated on a per pixel basis by using NDVI values to determine appropriate roughness values and using remotely-sensed estimations of daily net radiation. Decadal cumulative estimates and 5-day cumulative estimates with Meteosat were also tested with success (Seguin *et al.*, 1991). This method needs to be expanded to take wind-speed effects into account. The authors feel, however, that the method is only applicable to regions with pure pixels since the *B* constants are only derived for uniform crops. This is a serious constraint for operational applications in the Sahel.

Lagouarde's work, although innovative, is the most empirical and the link between NDVI and surface roughness is somewhat tenuous. Furthermore, the author's concerns about the method over mixed-crop pixels (as opposed to pure pixels) is legitimate. Most Sahelian pixels will contain a combination of sparse crop coverage and natural vegetation. Rosema's approach is more rigorous but the key constant *B* seems somewhat weakly described for a satellite pixel. Rosema's technique has already been tested with success in portions of the Sahel, however. The use of a full Penman-Monteith calculation does provide estimations for cloudy pixels (even though it is computationally expensive). Perhaps in a spatially stratified or GIS approach (such as Berkhout, 1986), an optimal or representative *B* constant can be prepared for similar land strata. Crop-covered land strata are regions with relatively similar soils, topography and land use practices, and therefore should contain crops with similar heights and roughness. Isolation of land use practices such as subpixel fields can clarify the mixed-pixel case. Reference strata *B* constants can be calculated frequently enough to represent the changing structure and roughness of the crop canopy throughout the growing season. A range of *B* values representing different wind speeds over each facet would also need to be archived. Deterministically-derived reference *B* constants can be compared to test constants derived from field measurements. These reference *B* constants could be used to calculate evapotranspiration at all pixels over a range of pixel temperatures within each facet. The *B* constant used in the approach of Thunnissen and Nieuwenhuis (1990) and Caselles et al. (1992) is particularly appealing as it is less sensitive to atmospheric conditions. Furthermore, this method relies on optimal temperature techniques and does not require ground-based and interpolated values of air temperature (which, given the meteorological station sparsity in the Sahel, are certain to introduce gross errors).

4.4. SOLAR RADIATION/IRRADIANCE ESTIMATION

The accurate estimation, at a regional scale, of global (from all directions) and total (in the visible and near infrared) solar radiation incident at the Earth's surface is another component of yield-estimation models. This variable allows the estimation of photosynthetically-active radiation (PAR). The effect of atmospheric nebulosity and turbidity has to be taken into account. Some methods have been developed to derive the incident radiation from meteorological satellite data. There are two main approaches:

1. The estimation of incident radiation from the reflected radiation measured by satellite (Brakke and Kanemasu, 1981; Kerr and Delorme, 1981; Dedieu *et al.*, 1983); this approach is limited by the difficulty of accounting for atmospheric perturbations.
2. The estimation of global solar radiation from a cloud index. For instance, the Heliosat program analyzes multitemporal data from geostationary satellites to derive albedo, apparent albedo and maximum of the albedo values for clouds at the scale of the planet (Diabate *et al.*, 1989). A total atmospheric transmission factor is derived. An estimate of solar radiation received at the ground is simply the product of the atmospheric transmittance and the horizontal irradiance at the top of the atmosphere.

4.5. SOIL NUTRIENTS STATUS ESTIMATION

Remote-sensing applications for the identification and mapping of soils across the Sahel have not been developed on the sub-continental scale. Reliance on ground data and extensive field work makes soil mapping a long and costly process, yet the information is a critical input to crop-production estimation. In the dry, northern regions of the Sahel, water availability is the limiting factor in both primary and agricultural production. Vegetation on northern rangelands characteristically makes efficient use of available nutrients in the soil and the paucity of rain serves to protect valuable nutrients from dilution. However, further south at latitudes with higher annual precipitation, the level of nutrients and their availability to plants is the critical factor. The southern region of the Sahel is more commonly subject to agricultural and animal production practices that strain the carrying capacity of the land and exhaust nutrients that are already at low levels (van Keulen and Breman, 1990). There is a measured Sahelian gradient in soil nutrients that is similar to the rainfall gradient, but this information is probably too general to be of use as an input to crop-growth models where soil nutrient information must be extremely detailed and site specific (van Keulen and Breman, 1990). In the absence of comprehensive soil maps for the Sahel, the nutrient gradient could be keyed to the latitudinal stratification of precipitation regions or to agricultural practices of different ethnic groups in a spatial stratification of the area according to physiographic units.

4.6. REMOTELY-SENSED VEGETATION INDICES

4.6.1. *Interpretation of vegetation indices*

Remotely-sensed vegetation indices are arithmetic combinations of spectral responses in different wavelength bands which emphasize a particular feature of the vegetation. They have become widely-used tools in the analysis of remotely-sensed data for vegetation studies in general. The most commonly used is the normalized difference vegetation index (NDVI), which is $IR-R/IR+R$. Empirical studies have successfully correlated NDVI with variables related to: (1) canopy quantities (leaf area index, above-ground biomass, per cent canopy cover, etc.); (2) state of the vegetation (stress, vigor, chlorophyll content, etc.); (3) solar radiation interaction with plant canopies (intercepted or absorbed photosynthetically active radiation, etc.); (4) vegetation moisture (leaf water content, water satisfaction index, etc.); (5) ecological variables (rainfall, potential and actual accumulated evapotranspiration, surface temperature); and (6) instantaneous rates associated with the activity of the vegetation (rates of photosynthesis, transpiration, carbon dioxide exchange). According to this last group of interpretations, time integrals of vegetation index data can provide estimates of biomass production. This wide diversity of interpretations may be viewed positively as a sign of the rich information content of the NDVI, and its value as a general biospheric indicator, but it also reveals the ambiguity of the nature of the NDVI.

The relationship developed between spectrally-derived vegetation indices and the biophysical properties of canopies is almost always indirect. It is clear that most of the variables with which the NDVI has been associated are closely interrelated (they all have to do with vegetation canopies, biomass development or ecological conditions), but they do not have exactly the same biophysical meaning. Theoretical analyses (Sellers, 1985, 1987; Tucker and Sellers, 1986; Choudhury, 1987; Asrar *et al.*, 1989) have analyzed the biophysical processes that justify the interpretation of the NDVI in terms of instantaneous rates associated with vegetation canopies—gross primary productivity and evapotranspiration. However, these theories do not support all empirical relations that have been established with NDVI. In spite of the availability of these modeling studies, the successful relationship between NDVI and biophysical variables only corresponds to large-scale first-order correlations, the exact physical significance of which still needs more precise analysis (Seguin *et al.*, 1991). In general, the NDVI cannot be considered as a measurement of biophysical quantities but should rather be treated as a dimensionless empirical objectifier (or an indicator) of such quantities.

4.6.2. *NDVI and APAR*

Several biophysical variables which have been correlated to the NDVI can be used in crop yield estimation models: leaf area index (LAI), absorbed photosynthetically-active radiation ($APAR$), total dry-matter production ($TDMP$), net primary productivity (NPP) and actual evapotranspiration (AET). The fundamental logic in terms of crop yield estimation is as follows:

$APAR = f(LAI)$,
$TDMP$ or $NPP = f(APAR, AET)$ and
$Yield = f(TDMP)$, f being a crop-specific function.

The leaf area index represents the area of foliar coverage per unit ground area and can be used in combination with incoming solar radiation to determine the amount of PAR which is intercepted by the canopy. Actual evapotranspiration can act as a surrogate measure for the relative effectiveness with which a canopy is able to utilize APAR. This combination of parameters can be used on an integrated or instantaneous basis to determine TDMP or NPP as long as there is adequate information on the conversion efficiency of energy to plant biomass for the existing crop type. Finally, if the relationship between biomass productivity and crop yield is known for the existing crop type, then a crop yield can be estimated based upon NPP or TDMP. The literature suggests that NDVI data are a better indicator of APAR than of LAI or biomass (Kumar and Monteith, 1982; Steven *et al.*, 1983; Asrar *et al.*, 1984, 1986; Sellers, 1985; Daughtry *et al.*, 1985; Choudhury, 1987). Thus, currently, the most reliable use of NDVI data in crop-growth models is as a quantifier of APAR.

4.6.3. *NDVI and evapotranspiration*

Because actual evapotranspiration is one of the best indicators of biomass productivity in the water-limited Sahelian environment, NDVI and evapotranspiration should be strongly correlated (Seguin *et al.*, 1989). Sogaard (1988) found a significant correlation between seasonally integrated NDVI and accumulated evapotranspiration (derived from satellite methods) in regions of dense biomass. In sparsely-vegetated regions, however, the relationship is less reliable. This inconsistency is believed to be due to the influence of soil color contamination on the NDVI values. Even in localized, densely-vegetated regions, although integrated NDVI can be used to provide end-of-the-season evapotranspiration maps, it is not suitable for forecasting. Satellite-derived evapotranspiration fluctuations precede NDVI variations (and thus biomass variations) by as much as 4 weeks, emphasizing the importance of satellite evapotranspiration monitoring for biomass estimation (Rosema, 1990).

5. Yield-estimation models

The biophysical data related to agricultural production need to be integrated in models in order to estimate or predict crop yields. Existing approaches to the problem of yield estimation vary from experimental methods which, while theoretically sound, present logistical problems in terms of acquisition of accurate surface data, to operational methods which may lack detail and accuracy, but provide some useful information in a timely manner. Experimental procedures tend to be deterministic in nature and require detailed information on the vegetation–soil–energy system. Operational approaches tend to be semi-deterministic or statistical in nature and require less-detailed data as input. It is necessary to select feasible scenarios for crop yield-estimation given the variables which can be accurately estimated from remotely-sensed data and which satisfy our spatial and temporal constraints. This includes the identification of a combination of data and models which will provide the highest possible accuracy or the best trade-off between accuracy and cost. We will examine deterministic, statistical and semi-deterministic approaches.

5.1. DETERMINISTIC CROP-GROWTH MODELS

A crop-growth model is a quantitative representation of the mechanisms and processes that determine the dynamics of a crop. These deterministic models are used to study the rate of growth of crops based on a description of photosynthetic activity, leaf area development, etc. and to analyze the influence of environmental factors on the growth of crops. Crop-growth models require daily estimations of input values for a large number of variables. Common variables necessary to run these models include intercepted photosynthetically-active radiation (IPAR), soil moisture holding characteristics, crop type, temperature, rainfall, crop structure, actual evapotranspiration (AET), biomass conversion efficiency and yield conversion efficiency. Some of these variables can theoretically be estimated using remotely-sensed data. Different models exist for different geographic contexts and different crops. For each type of model, the emphasis focuses on the main limiting factor(s) for that crop in that environment. Some of the main crop-growth models that have been used for semi-arid tropical agriculture are:

1. SORGF was developed in the United States for sorghum (Arkin *et al.*, 1976) and applied to semi-arid tropical regions (Huda *et al.*, 1987).

2. CERES-MAIZE, the most widely-used crop-growth model in the United States (Ritchie, 1985), has been tested for a variety of environments. du Pisani (1987) has applied this model to evaluate the impact of drought on maize yields in South Africa and to predict that yield.
3. WOFOST (van Diepen *et al.*, 1989) is a powerful and flexible numerical simulation model of crop growth which integrates physical and agronomic information. Model data requirements include site-specific information such as the starting date of crop growth; initial soil-moisture conditions; physical properties of the soil surface such as surface-water storage capacity and natural soil fertility; and more general data on climate, crop and soil characteristics. WOFOST computes yield under three growth constraints: light and temperature regime, water supply or soil nutrients supply. The selection of the constraint situation depends on the type of agriculture practiced (irrigated, rainfed or fertilized). This model has been applied, for instance, in Zambia (Wolf *et al.*, 1987; Azzali, 1990).

A purely deterministic approach for agricultural production monitoring would rely on one of these deterministic crop-growth models and on the estimation of all required input data on a daily basis, at the scale of the fields. This approach, while highly accurate, is impractical at the sub-continental scale. The estimation of all input data to simulate plant growth across the Sahel would require a very dense network of field stations with data-transmission facilities, and/or highly performant remote-sensing systems to measure these variables from space. While we cannot exclude possibility that such an infrastructure will exist in the future, today the deterministic approach is not feasible in the Sahel, at least at a sub-continental scale.

5.2. STATISTICAL AGROMETEOROLOGICAL MODELS

Agrometeorology is the real-time application to agriculture of the spatially synoptic meteorological information, related to the present weather and, when possible, related to the forthcoming weather (Franquin, 1984). Two main agrometeorological approaches are possible: statistical or semi-deterministic approaches. The semi-deterministic approach will be examined in Section 5.3. The statistical approach relies on current meteorological data which are analyzed in terms of potential crop yield based on archival data. The functional relationship between climatic data and crop yield is not developed as such. Crop yields can potentially be estimated using statistical relationships with rainfall or the NDVI, two variables that can easily be derived from remotely-sensed data. The paucity of archival data is the main limiting factor of the feasibility of such analysis. Many countries in the Sahel do not have consistent records of remotely-sensed and/or meteorological data for this century.

5.2.1. *Rainfall and crop yield*

Some studies have explored the direct correlation between rainfall and crop yield. In Botswana, where rains are marginal and unevenly distributed, Vossen (1988) has found that statistical relations between average annual rainfall and crop yield are improved by using a weighted average of the three stages of the rainy season (early, mid and late). While there is no accounting for distribution effects of rainfall, evapotranspiration, soil capacities, runoff, etc., this method offers the advantage of depending on readily accessible data. Seguin *et al.* (1989) conducted a study to assess the use of meteorological satellite data to monitor crop-water conditions in the Sahel. Their work included a correlation study between rainfall and crop yield, which was not found to be satisfactory.

Justice *et al.* (1991) have investigated the synergistic use of satellite data in vegetation monitoring, using Meteosat data to derive rainfall estimates and AVHRR data to interpret vegetation response via the NDVI. Rainfall estimates and NDVI show comparable spatial variations and a similar north-to-south gradient. Furthermore, the researchers identified time lags between rainfall and vegetation development. While acknowledging that crop-yield estimation is not yet feasible using this method, these authors demonstrate the potential of using satellite datasets to identify areas where production potential is not being met.

5.2.2. *NDVI and crop yield*

For crop assessment in semi-arid Africa, the NDVI can be interpreted or utilized in several different ways. One approach is *empirical* and relies on linear regression models between final crop yield and instantaneous NDVI. The correlation coefficient between NDVI and crop yield is maximal at the heading of the plant (Johnson *et al.*, 1987). The main limitation of this approach is the instability of the relationship through time. Bartholomé (1988) has shown that the accumulation of the NDVI over the reproductive phase allows the stabilization of the relationship. The parameters of the regression can be defined *a priori* for yield forecasting (Bartholomé, 1988; Azalli, 1991; Rasmussen, 1992). A regression analysis requires the assumption that a functional relation exists between the variable to be explained (NDVI) and the explanatory variable (crop yield or total biomass). The NDVI is thus implicitly interpreted as a dependent variable which is an "effect" of the crop yield. Other vegetation productivity models accept NDVI as an independent variable, i.e. a variable which is interpreted as a cause. However, since NDVI reflects the development of the plant during the growing season, it is not independent of other growth parameters such as energy and water available for plant growth (Cihlar *et al.*, 1991). Tucker *et al.* (1980) used the NDVI curve to determine the period of highest correlation with final yield, which corresponded to the maximum amount of leafy biomass present. Subsequent research by Hatfield (1983) revealed that 90% of reproductive dry matter is accumulated at the time the value of the vegetation index is 0·5 of the maximum, which occurs at grainhead emergence. These studies help to define the appropriate time period for integration of the NDVI in different environments.

A second approach is *statistical* and is based on pluriannual archives of seasonal series of NDVI calculated from AVHRR data (LeComte, 1989). The seasonal development of the NDVI at a location during a given season is compared to the "normal" spectral development, statistically derived from the pluriannual data set. Any departure from the "normal" situation is interpreted in terms of climatic events or cropping practices and is related to variation in expected yield. In this approach, the NDVI is interpreted as being an empirical indicator of the state of the vegetation and allows a qualitative monitoring of vegetation stress (Tucker *et al.*, 1980; Johnson *et al.*, 1987).

Use of the NDVI for crop-yield estimation and forecasting in semi-arid regions of Africa is a promising application, but it has yet to be developed operationally (Prince and Justice, 1991). A major constraint to this approach is the lack of consistent archives of NDVI data over Sudano–Sahelian regions. The compilation of such archives is a priority for several institutions operating in the region. Also, given the high fragmentation of the landscape in the African regions of rainfed agriculture, AVHRR NDVI data (at 1-km spatial resolution) integrates natural vegetation with cultivated fields (Philipson and Teng, 1988). It thus assumed that these two classes of vegetation spectrally behave according to a similar seasonal pattern. Azalli (1990) has shown that it is possible to mask the non-agricultural domain on low spatial resolution data (AVHRR LAC or GAC) by superimposing a land cover classification performed on higher resolution data (Landsat or SPOT) in order to analyze the NDVI seasonal development curve of cultivated fields separately from the surrounding natural vegetation. Maselli *et al.* (1992) have used a geographical standardization process to remove differences in local environmental factors from the NDVI.

5.3. SEMI-DETERMINISTIC AGROMETEOROLOGICAL MODELS

While determinsitic models focus on exhaustively simulating the natural environment, and statistical models rely on the empirical monitoring of vegetation, semi-deterministic models attempt to strike a balance between these two approaches in order to find the best trade-off between accuracy and operationality. Semi-deterministic approaches in agrometeorology follow two steps. First, temporal series of easily accessible climatic variables, such as hydric balance, temperature or solar radiation, are used in an attempt to characterize yield as a function of either stress degree days or crop-water balance through causal relationships. Second, a statistical relationship is established between predicted and observed yield through a regression model. Two categories of semi-deterministic models will be discussed.

5.3.1. *Productivity model*

A simple crop-growth model has been used for an operational crop-yield estimation: the dry-matter accumulation of a crop is calculated from the integral, through the growing season, of the photosynthetically-active solar radiation (PAR) incident on the crop canopy multiplied by the absorbed fraction of PAR and by a conversion efficiency coefficient (Monteith, 1977):

$$\text{Phytomass} = \int \text{PAR APAR } \varepsilon \, dt .$$

The parameter ' ' represents the efficiency with which specific crop types convert energy into biomass. The NDVI can serve two possible functions in the type of model outlined above. First, this index may be useful for estimating APAR by a linear relationship that has to be empirically calibrated:

$$\text{APAR} = a + b \text{ NDVI} .$$

The estimation of APAR through the NDVI is the statistical component of the semi-deterministic model. Second, the NDVI can be used to identify the temporal bounds of that portion of the crop-growth cycle for which the phytomass produced can best be related to crop yield (see Section 5.2.2). For example, Henricksen and Durkin (1986) established the length of the growing season in Ethiopia using AVHRR NDVI data.

Although this model has been used in the Sahel (Bartholomé, 1988; Imbernon *et al.*, 1990), its physical basis is not quite appropriate to semi-arid regions. This model is based on a proportional relation between dry-matter production by a crop and the amount of solar radiation absorbed by the foliage of that crop, while the main limiting factors to production in semi-arid regions are water availability and soil nutrients, not explicitly accounted for in the above productivity model. Moreover, Prince (1991) points out the difficulty in determining the efficiency index "ε", or the rate at which a plant canopy converts APAR into biomass. This parameter can probably not be considered constant and should be modified by parameters reflecting departure from optimal efficiency due to physical stress, and the proportion of assimilate used for maintenance respiration. This can be especially problematic if biomass estimates (or crop-yield estimates) are attempted using low spatial resolution satellite data, if the crop cover is heterogeneous or if environmental conditions vary over the landscape of interest. Finally, Demetriades-Shah *et al.* (1992) demonstrates that crop growth and radiation interception will always be well correlated, even without a strong causal relationship, because: (1) anything increasing in size intercepts more radiant energy, for a simple geometric reason; and (2) any series of accumulating values are highly correlated, for an arithmetic reason.

When using remote sensing to estimate input data for more complex crop growth models, several problems arise. If a single satellite source is used to estimate several parameters, independence among the derived variables may be compromised. This can also be a problem if the NDVI itself is used as one of the input variables since it is correlated to many ecological variables. Also, errors in the estimation of input variables using remote-sensing models may be compounded and propagated through an agricultural yield model resulting in unacceptable errors in the final output. For example, small errors in the NDVI can translate into large errors in inferred biophysical processes. The most obvious source of error is that associated with the natural variance in the statistical relationship between remotely-sensed data and the variable of interest. Errors can also arise for other reasons, including the reflectance precision of the sensor, viewing geometry, atmospheric conditions, anisotropic properties of surface reflectance and atmospheric scattering, image-processing procedures (e.g. maximum value compositing) and between-scene registration (Goward *et al.*, 1991).

5.3.2. *Yield-reduction model*

Yield-reduction models estimate the ideal production for a certain region (Y_n) from records of previous "normal" years and then use various environmental monitoring schemes to reduce that ideal in order to predict the crop yield of the current season (Y). Rather than monitor the vigor of the vegetation, semi-deterministic schemes monitor the stresses that can affect the final yield of the harvest. A general format of this model is:

$$Y = a + b\ Y_n - c\ (\text{Hydric stress}) - d\ (\text{Thermal stress}),$$

with a, b, c and d being calibration parameters. In the case of the Sahel, hydric stress is the primary culprit of low yields. It can be measured as the difference between potential and actual crop evapotranspiration (Frere and Popov, 1986). Thermal stresses further affect the vegetation by reducing a plant's ability to retain and process water. Therefore, available (post-runoff) moisture and evapotranspiration govern the growth and final yield of a crop.

Stress models primarily use daily precipitation, minimum and maximum temperatures and soil conditions to measure actual evapotranspiration of a specific crop and determine moisture availability for crop growth. By remotely sensing these parameters, evapotranspiration estimates can be monitored and their impact on crop yields evaluated. Some operational methods rely primarily on satellite-detected temperatures as well as routine meteorological ground measurements to obtain a satellite-derived stress index (Boatwright and Whitehead, 1986). Other non-remote-sensing methods monitor the cumulative water balance throughout the growing season and generate a water satisfaction index to determine whether a certain crop is being affected. For example, the Global Information and Early Warning System on Food and Agriculture under the FAO publishes a cumulative water balance or water satisfaction index which gives a general indication of the per cent of potential yield which can be expected following water stress (Frere and Popov, 1986). Further reductions in crop yield can be introduced if disease or insect damage is noted. Such approaches may be general in nature and fraught with accuracy problems, but they provide some timely indication of crop condition and have an unambiguous biophysical basis. They are better adapted for regional scales. If combined with remotely-sensed data to measure hydric stress (through evapotranspiration) and thermal stress (through surface temperature), yield reduction models offer the greatest potential for agricultural production monitoring, though there is little experience with this type of integration.

6. Information system

We have described methods for data acquisition and data analysis for agricultural production monitoring. However, an information system is composed of four other subsystems: database management, data input and storage, information output and information use. Geographic information systems (GIS) can combine all four subsystems into one common database and employ one software package. The incorporation of satellite data in the GIS promotes the use of a raster-based system (grid database). Although the initial financial and time costs of setting up a GIS is high, the long-term benefits of data manipulation, update and output justify these costs. Moreover, a GIS is flexible and can be easily adapted to rapidly-evolving scientific methods and technological capabilities. Berkhout (1986) has developed the concept of the integration of a crop-growth model and a GIS as a tool for famine early warning. He concluded that extensive field observations were still required in addition to the processing of remotely-sensed data in order to quantify the combined effect of all land entities and farm practices on specific crops. The number of field observations could be reduced with the calibration of simulation models over a number of years. This requires the availability of archives of data.

Given the real-time requirement of the application and the decentralized character of the data (especially ground data), a powerful data transmission system has also to be implemented. The volume of data to be transmitted in order to monitor agricultural production at a regional scale may require unrealistic data transmission capabilities for the present telecommunications infrastructure of the Sudano–Sahelian region.

7. Perspectives and future needs

Currently, all the systems to monitor agricultural production in the Sahel at a regional scale are qualitative and based on a statistical or empirical approach. A purely deterministic approach is not feasible today. The bottleneck for such an approach is not situated at the level of models but rather at the level of the infrastructure for data collection. However, at the state of the art, this study is showing that a semi-deterministic approach is possible and that several key variables can be estimated reliably from remotely-sensed data. In order to implement these semi-deterministic approaches and to improve the scientific and technical expertise in agricultural production monitoring in the Sahel, we make the following recommendations:

1. More ground data collection networks are needed in the Sahel. National and regional networks of meteorological, agronomic and ecological stations should be expanded in order to: (1) grasp better the spatial variability of environmental variables in the Sahel; and (2) create archival data to increase the reliability of statistical approaches in the future.
2. Telecommunications infrastructure should be enhanced wherever possible. Funding for infrastructure improvements should always include a training component.
3. Projects for soil and topographic mapping, in digital format, should be promoted for integration with GIS. The mapping and monitoring of this variable, which has a considerable influence on crop yields, is currently the weakest part of an agricultural production monitoring system. Also, a better understanding of per-pixel surface roughness is the primary requirement for an accurate deterministic pixel-by-pixel evapotranspiration calculation. Remote-sensing methods for determining surface roughness (perhaps active systems instead of passive), wind speed and soil cover routinely throughout a growing season will dramatically increase accuracies. Per pixel soil attribute information will also improve evapotranspiration calculations.
4. Many remote-sensing models require detailed ground data and, while these models have been tested under experimental conditions, their operational potential still needs to be verified and validated through further research. There is a need to scale-up from empirical field studies and model simulations to testing the use of satellite data on a regional scale.
5. The co-operation among researchers working on related projects should be promoted. Setting up different systems in different regions is counterproductive when the goal is to solve problems at the sub-continental scale. Moreover, by its interdisciplinary character, the research on agricultural production monitoring is currently scattered. Different teams develop some pieces of the system, but very few people work on the integration of the pieces and on the validation of the whole chain of operations to estimate reliably agricultural production in a timely fashion.

The initial research leading to this paper was undertaken at da Vinci consulting (Belgium) by Eric Lambin and was funded by the Joint Research Centre of the Commision of the European Community (study 4027-90-07 ED ISP F). The research has been pushed further at Boston University.

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